WCRR 2025 THE BROADMOOR, COLORADO SPRINGS, CO, USA NOVEMBER 17-21, 2025

Holistic Modeling and Optimization of Hydrogen-Powered Trains for Zero-Emission Railway Operation

Moritz SCHENKER[1], Steffen WIESER[1], Isabell MOSER[1], Mathias BÖHM[1]
[1]German Aerospace Center (DLR) – Institute of Vehicle Concepts, Stuttgart, Germany
Corresponding Author: Moritz Schenker (moritz.schenker@dlr.de)

Abstract
This study introduces a comprehensive modeling framework for optimizing hydrogen-powered trains to facilitate zero-emission railway operations. Focusing on the *Heidekrautbahn* project in Brandenburg, Germany, the work addresses the unique challenges associated with hydrogen-powered trains by developing a modular python-based simulation environment. The approach enables easy and quick testing of operational strategies using simulative results before implementing only the most promising ones into actual operation. Four core components comprise the framework: (1) driving dynamics, (2) heating, ventilation, and air conditioning (HVAC), (3) energy management systems (EMS) and (4) hydrogen refueling processes. Collectively, the entire energy chain of hydrogen from refueling to traction force generation is represented. In this work, two key components, the driving dynamics and energy management modules, are validated using real-world measurement data from the *Heidekrautbahn* project. The sub-models are able to replicate the vehicle's behavior, demonstrating high fidelity with errors below 5% compared to measurement. Leveraging the model, energy-saving potentials in the order of 10% for improved driving and energy management strategies were quantified. By means of simulation-based testing, efficient yet easy to implement operational strategies with increased range and flexibility are chosen. This research, conducted alongside the implementation, enhances the in-depth understanding of operation with hydrogen-powered trains, potentially improving their performance and positioning them as viable alternatives to traditional diesel-powered counterparts.
Keywords: hydrogen-powered trains, simulation validation, energy management, optimization potentials

1. Introduction

Railway electrification with catenary is not possible or economically feasible for all available tracks. Therefore, in the *Heidekrautbahn* project [1] an emission-free alternative is implemented in Brandenburg, Germany as the first hydrogen-powered networks of passenger railway vehicles with local, green hydrogen. The challenge of reliable access to sustainable energy is addressed by electrolyzers, utilizing the extensive availability of wind energy. Currently, there is a lack of experience and knowledge in the operation of hydrogen-powered trains, since application only started in recent years. Processes which are standard procedure for diesel-powered trains such as refueling scheduling need to be rethought. Similarly, driving characteristics and optimal operation points of the drivetrains can significantly differ between these train types. This means that application of conventional driving strategies and timetables can be inefficient for hydrogen-powered operation and may lead to unnecessarily low vehicle availability.

The primary goal of this accompanying research is to simulate and evaluate the technical relationships and optimization potentials in the operation of the trains and refueling stations. A digital model of the hydrogen railway vehicles shall support the knowledge gain and competitiveness against diesel trains. Therefore, a novel, holistic model approach is chosen, which includes all relevant steps of the hydrogen, from refueling over driving

strategies to the energy management on the train. It aims to promote the level of understanding and thus identification of improvement potentials for availability and energy efficiency of the vehicles.
The paper is structured as follows: a summarized description of the models, validation of the two main model components *Driving Dynamics* and *Energy Management* with measurement data from the *Heidekrautbahn* project, a discussion of optimization measures and finally the takeaways.

2. Methodology

The holistic model of the hydrogen energy flow from refueling station to propulsion of the train is built in python as a framework of interfacing modules (see Figure 1). These submodules include:
a) *Driving Dynamics*: the dynamic physical model of the train in its movement on the track with relevant external parameters, such as gradients, speed limits and timetable
b) *Heating, Ventilation and Air Conditioning (HVAC)*: a thermodynamic model of train compartment
c) *Energy Management System (EMS)*: the power control strategy and system on the train, applied on all powertrain components including fuel cell and battery
d) *Hydrogen Refueling*: a model of the hydrogen tank during the refueling process
The modules are built with clear separation of functionality, but predefined interactions which enable an integrated, single simulation run. This reduces susceptibility to errors and allows for fast results through automation.

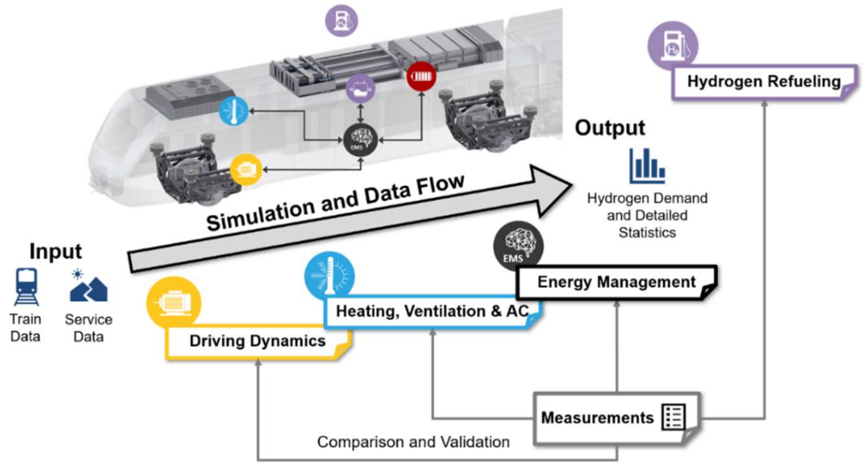

Figure 1: Schematic illustration of the data and simulation flow throughout the holistic train model.

In this work, the focus is put on the two modules *Driving Dynamics* as well as *Energy Management* as they are the key modules in the determination of the hydrogen demand. Traction demand is usually predominant when compared to HVAC and auxiliaries. Furthermore, EMS plays a crucial role in how efficiently this energy demand is supplied. Both modules are newly built, based on experience from previous in- house models [3-4].

2.1 Driving Dynamics Module

In this module, a speed profile and the corresponding mechanical power profile at the wheel are determined, based on route and vehicle data. This part of the simulation environment therefore refers to the dynamic interaction with the environment and the route, and thus to the mechanical part of energy modeling. All electrical power flows in the train are handled in the Energy Management module.
Detailed route data serves as the basis of the simulation: timetable, maximum speeds, gradients, curve radii, and electrification. The dynamic behavior of the vehicle is determined by its weight (m_{total} - static and rotational), length, resistance coefficients, traction and braking force characteristics (mechanical and electrodynamic for recuperation) as well as limits for speed, acceleration, deceleration and jerk. Based on this data, the equation of motion is solved to determine the longitudinal dynamics of the train:

$$\dot{v} = \frac{F_{\text{traction}}(v) - F_{\text{resistance}}(v,s)}{m_{\text{total}}}$$

The maximum force at the wheel F_{traction} is determined by the current speed v from the traction or braking force characteristic. The resistance force $F_{\text{resistance}}$ is speed and position dependent and consists of gradient, curve, and rolling resistance, with the latter two approximated using the Röckl and Davis formulas [5].

To determine the speed profile, a rule-based approach with different phases is chosen:

- Acceleration phase: Within the constraints of route and vehicle, the maximum available force is applied to the wheels. The acceleration can also be modulated to a percentage of the available force.
- Constant speed (cruising): A certain speed is maintained through adjustment of the traction force.
- Coasting phase (optional): The vehicle is allowed to coast without applying force.
- Braking phase: Within the constraints of route and vehicle, a given amount of the available braking force is applied. Additionally, the priority can be set from mechanical to electrodynamic braking to recover as much energy as possible.

From these driving phases, three different rule-based driving modes are currently implemented (see Figure 2, left), with further modes possible:

- *All-Out* driving: Acceleration, constant speed at the speed limit and braking phases are combined such that the vehicle arrives at the next station as quickly as possible. This driving style is time-optimized and therefore energy-intensive with maximum speeds.
- Timetable-compliant driving with *Reduced Velocity*: Acceleration, constant speed at reduced speed, and braking phases are combined, with the level of the constant speed phases adjusted to the time buffer between *All-Out* and the scheduled time.
- Timetable-compliant driving with *Coasting*: By combining all four phases mentioned above, a trajectory can be generated that maintains the timetable while reducing the net energy requirement at the wheels compared to the *Reduced Velocity* mode through the use of coasting.

With combinations of these modes, realistic driving behavior can be replicated in a simulative manner. Additionally, rule-based driving strategies present easily applicable optimization measures for manually driven vehicles. Compared to dynamically optimized, complex speed trajectories, the combination of pre-set driving phases can be applied in a straight-forward manner by train drivers in today's operation, e.g. through driver advisory systems.

2.2 Energy Management Module

In this module, the power at the wheels from the previous module is used as input. Together with auxiliary demands, component specifications and an EMS logic, the hydrogen demand is simulated. To accurately determine this demand, the following power balance equation has to be balanced (considering the efficiency characteristics of all electric components on the drivetrain):

$$P_{\text{traction}} + P_{\text{aux,HVAC}} + P_{\text{rheostatic}} = P_{\text{fuel cell}} + P_{\text{battery}}$$

The distribution between fuel cell and battery is not predetermined and must be determined by the EMS in such a way that the desired boundary conditions are met. These may include, for example:

- Balanced state of charge (SoC) of the battery at the beginning and end of a cycle
- Compliance with maximum C-rates for the battery
- Avoidance of certain SoCs, especially very low or very high
- Avoidance of highly dynamic fuel cell operation
- Reduction of hydrogen demand by efficient power control

EMS for hybrid vehicles can generally be divided into offline and online algorithms. Offline-EMS include optimization-based and rule-based approaches, while online-EMS are based on real-time optimization, predictive, and learning-based approaches [2]. For hybrid rail vehicle applications, offline algorithms are very suitable due to the strongly repetitive character of operation. Often, rule-based approaches such as finite-state machines (FSMs) are used. These provide a fixed fuel cell power output based on the state, e.g. based on the power demand and battery SoC (see Figure 2, right). Similar to the driving module, a rule-based approach was chosen to represent the real EMS within the project. However, multiple different EMS are implemented in the model and can be applied for different kinds of operation scenarios and to identify optimization potentials.

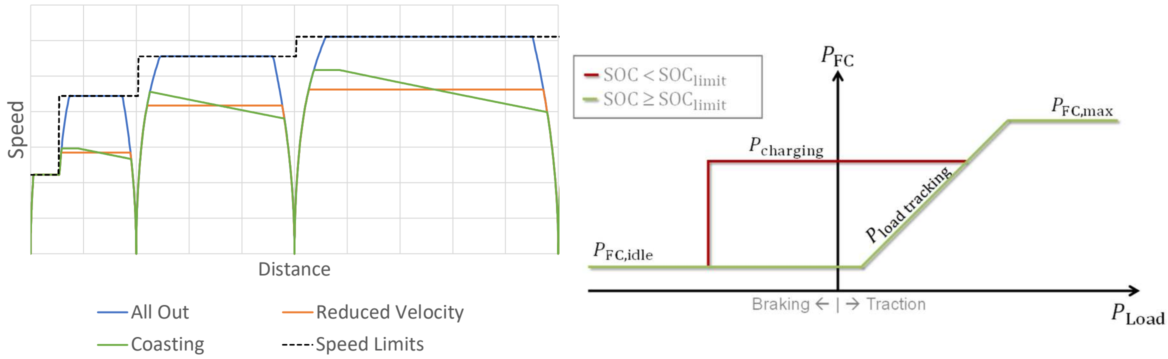

Figure 2: Left – Speed trajectories for different driving styles. Right – Exemplary energy management strategy for fuel cell power based on the current load and battery state of charge.

3. Results - Validation

The model is parametrized and validated within the project with data from real train operation of the existing Siemens Mireo Plus H hydrogen trains. Seven trains operate on the Heidekrautbahn since December 2024 [1] and data will be collected from the trains as well as the refueling station over several years. Physical parameters like speed, hydrogen consumption, as well as power and temperature at various components of the powertrain are measured and used as reference for the simulated values. With the early state of data collection and processing within the project, the validation process in this publication is based on characteristic sections. The modules *Driving Dynamics* and *Energy Management* are validated individually to avoid error propagation.

First, a characteristic driving section was chosen in which clean acceleration, cruising and braking phases are combined. Based on route and train data as well as the force control by the driver, speed and acceleration trajectories were simulated and compared to the measured data (see Figure 3, left). Qualitatively, there is satisfying accordance between them. In all three phases, the simulated data is "smoother". This is due to data noise in measurements, but also because of the manual operation, which can never be fully precise or consistent. Quantitatively, the speed trajectory has an average absolute error of 1.3 km/h, with a root mean square error (RMSE) of 1.6 km/h. The absolute deviation in acceleration is 0.037 m/s² and the RMSE 0.055 m/s².

For the EMS, a longer section with roughly constant fuel cell input power was chosen (see Figure 3, right). The measured power of auxiliaries and traction demand was used as input for the model. Calibrating the efficiency characteristics of the model components, the power required by the battery during the measurement could be replicated within the model, leading to an accurate determination of the battery SoC. For the SoC, the measured data has rather coarse resolution of data values, thus the simulated curve differs in spots, but approximates the behavior well. The simulated battery power follows the measured data very well. Deviations can be found in peaks and slight systematic offsets. For different orders of magnitude of power, the offset between the two lines varies due to load dependent efficiency approximation. Quantitatively, the battery power has a mean deviation of approximately 2.0% of its maximum power during the section, which corresponds to a RMSE value of 4.3%. The SoC deviates with 0.31% in absolute values and 0.38% in RMSE. The overall hydrogen consumption matches the measured data, which was to be expected during the constant fuel cell power phase.

With all deviations below 5% of the maximum values in the respective section, the model could be calibrated successfully and is able to reproduce measured data for characteristic operational sections. During the project phase all submodules will be validated and the procedure will be extended to the growing data set. With the model matching the real hydrogen demand, it is expected that it shall be able to predict required hydrogen consumption for optimized operational strategies as well.

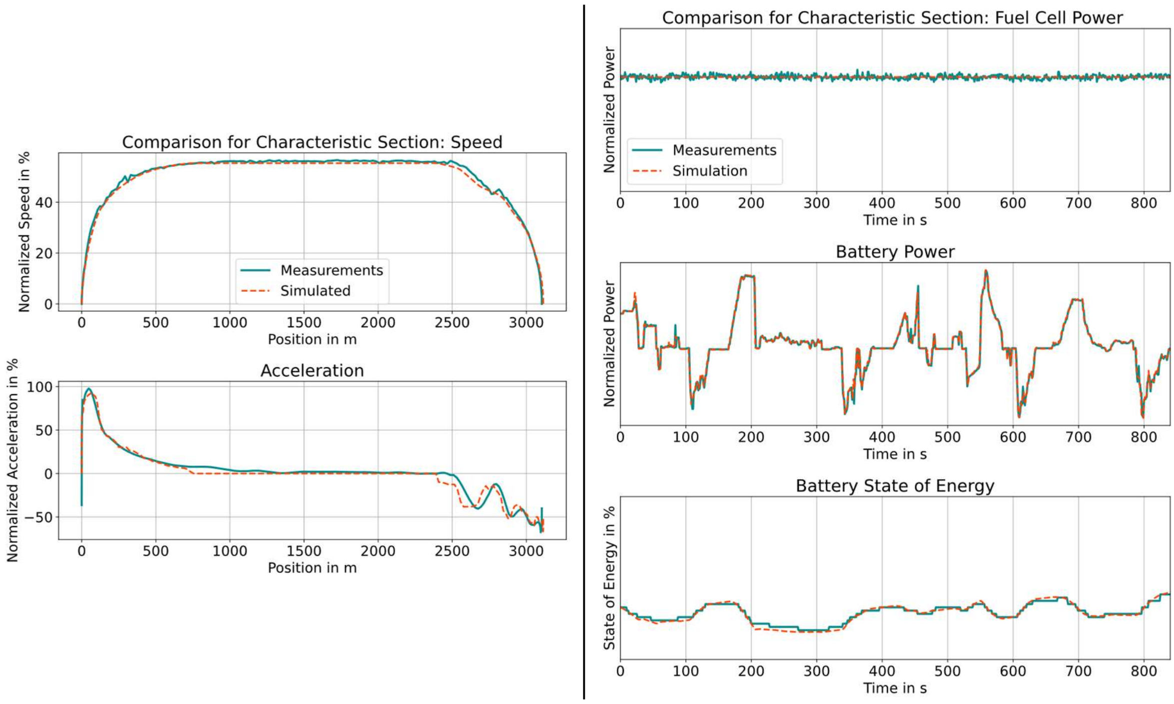

Figure 3: Left – driving dynamics simulation of speed and acceleration over distance compared to the measured data. Right – Energy management simulation with fuel cell power, battery power and battery state of energy over time in comparison with measured data.

4. Outlook - Energy Efficiency Measures

One major use case of the holistic model is to identify optimization potentials in operation. A key target figure is the hydrogen consumption. With energy efficient operation, range and flexibility of the vehicle are increased, leading to cost reductions for hydrogen supply and higher availability. To analyze the energy flow on the vehicle, energy sources, sinks and all losses are quantified. In order to increase efficiency, the most evident options are to either reduce the demand (traction and/or auxiliaries) or the losses (i.e. utilize more efficient operation points). These two major approaches can be tackled with the presented sub-models. Compared to the use of conventional, rule-based driving and energy management strategies in current operation, potential improvement measure can be tested in a simulative manner.

To demonstrate this, the three different driving styles mentioned above were tested against each other. While the *All-Out* style is the fastest, it also has the highest traction demand and prioritizes mechanical over regenerative braking, thus missing out on potential energy recovery. On the roughly 1 h operational scenario, *Reduced Velocity* and *Coasting* led to 9.1 and 11.2% reductions in traction demand, respectively. This decreases overall hydrogen demand, but also battery stress, since acceleration phases are shorter and more braking energy is recovered, which avoids deeper discharges of the battery.

Similarly, different EMS strategies were tested on the same scenario. It was found that the operation point of the fuel cell has major impact on the overall efficiency. If operated in higher power levels, not only the fuel cell efficiency decreases, but the battery is saturated during most of the ride, unable to store incoming braking energy. It is therefore more efficient to charge the batteries either with a lower fuel cell power or optimally during idle times of the train. The exact operation of the fuel cell also has a significant effect, e.g. preference of constant power, following the load or the possibility to turn the fuel cell off during operation. The test cases have shown a 13.7% decrease in overall hydrogen consumption between the shown EMS and the one from Zhang et al. [2]. Besides the improvement potential demonstrated here, it is also worth mentioning that a very

simple EMS with high fuel cell power levels can be extremely inefficient with exceedingly high increases of up to 40% in hydrogen demand. It is therefore crucial to analyze the EMS.
With the fully validated toolchain, it is the aim to find a suitable driving and EMS strategy during project time with easy to apply measures that can be introduced into ongoing operation, e.g. manual driving and fuel cell control. These measures will be communicated to the operators for discussion and potential implementation.

5. Conclusion and Outlook

In the accompanying research of the Heidekrautbahn project, a holistic model was built for simulation and evaluation of technical relationships and optimization potentials in the operation of hydrogen-powered trains and refueling stations. The digital model of the hydrogen railway vehicles has been successfully validated using data from real train operation. With deviations below 5%, the ability to accurately replicate the energy flows and hydrogen consumption of the trains could be demonstrated. The results of this study have shown that there are simple, rule-based measures for reducing hydrogen consumption through improved driving strategies and energy management strategies. Both, the utilization of driving adaptations with reduced speed or coasting phases and optimized EMS strategies can lead to decreases in energy demand of up to 10%.
The recommendations for energy- and thus cost-efficient operation can be used on one hand to reduce the demand of hydrogen as a rare and valuable resource and, on the other hand, to gain operational flexibility and avoid failures, thus increasing availability. Using the presented models, operators and infrastructure managers can be supported in transition to emission-free railway transport, while the findings can serve as blueprints for future implementations. In addition, the database offers a reference for operational knowledge with hydrogen trains collected in various operating situations.
In this work, the model is tuned and parametrized for the trains used within the project. However, its capabilities extend beyond this scope. It is possible to simulate various train types, such as battery electric, pure overhead-line or bi-modal with respective energy management systems. Furthermore, besides the use case to rapidly implement and tests further driving styles or energy control strategies, it also allows to estimate the required component sizes of battery and fuel cell for specific use cases [4]. Finally, it is planned to include aging estimation in the future, to utilize this information in further cost reductions.

Acknowledgment

Accompanying DLR research funded by the Ministry for Economic Affairs, Labour, Energy and Climate Action of the state of Brandenburg, Germany (MWAE) under individual measure according to the ZiFoG program, application no: 80259660, duration: 08/2022-12/2035. The vehicle data of the Siemens Mireo Plus H is collected and provided exclusively for scientific purposes as part of the research project.

References

[1] Kreiswerke Barnim GmbH, "Wasserstoffschiene – Heidekrautbahn," https://wasserstoffschiene-heidekrautbahn.de/, accessed May 14, 2025.
[2] Zhang, F. et al., "Energy Management Strategies for Hybrid Electric Vehicles: Review, Classification, Comparison, and Outlook," Energies, Vol. 13, No.13, Article-No. 3352, 2020.
[3] Schenker, M., Kühlkamp, F., "Optimization Model for Operation of Battery Multiple Units on Partly Electrified Railway Lines", presented at IEEE 16th International Conference on Ecological Vehicles and Renewable Energies (EVER 2021), Monte-Carlo, Monaco, May 5-7, 2021.
[4] Scharmach, M., Schenker, M., Dittus, H., "Comparison of simulative methods for dimensioning of fuel cell-battery hybrid powertrains in FCH2Rail and VirtualFCS," presented at International Railway Symposium Aachen 2023, Aachen, Germany, November 22-23, 2023.
[5] Bosso, N. et al., "The influence of resistant force equations and coupling system on long train dynamics simulations," Proceedings of the Institution of Mechanical Engineers, Part F, Vol. 236, Issue 1, pp. 35-47, January 2022.